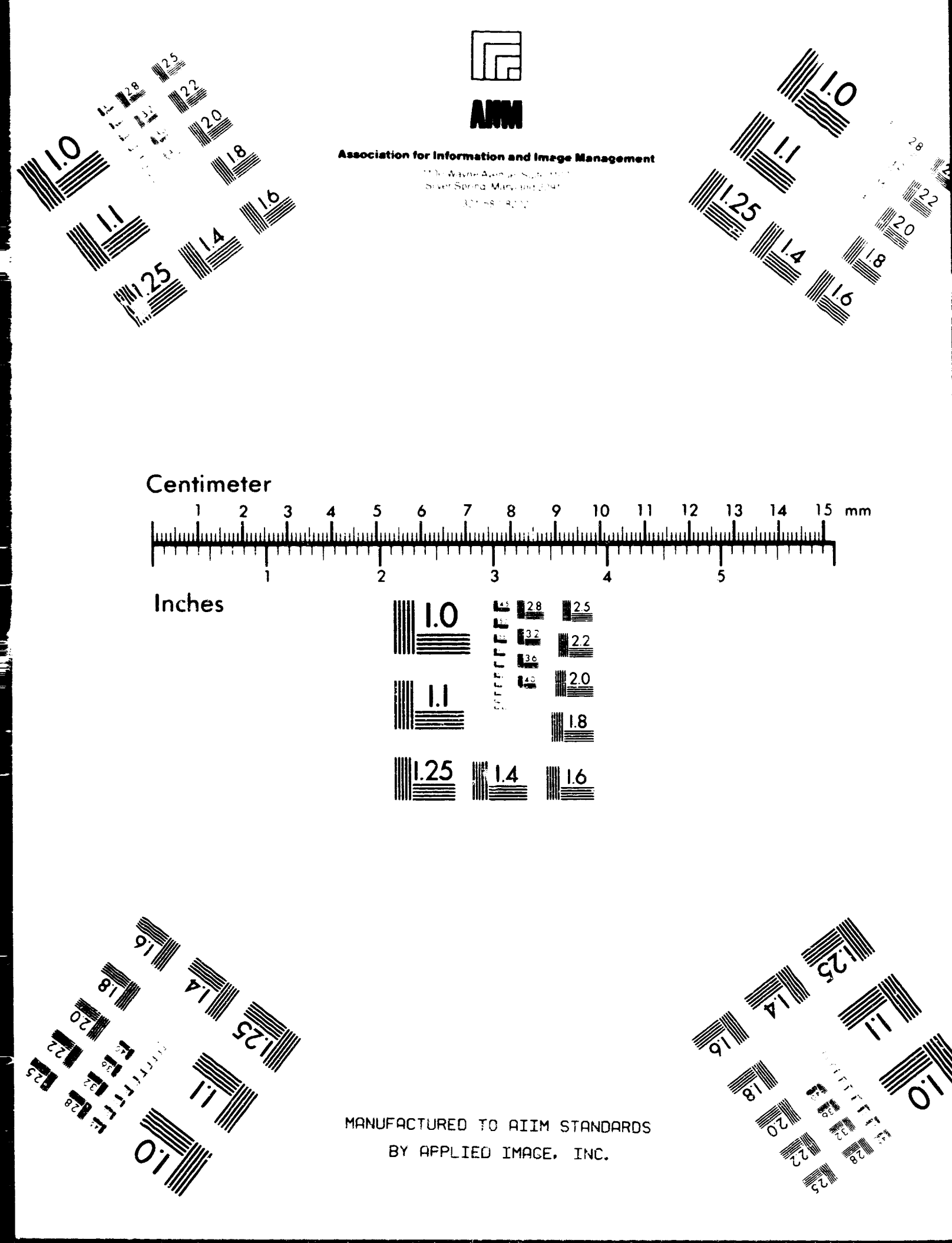
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Communications and Control for Electric Power Systems:

Power System Stability Applications of Artificial Neural Networks

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ABSTRACT

THIS REPORT investigates the application of artificial neural networks to the problem of power system stability. The field of artificial intelligence, expert systems and neural networks is reviewed. Power system operation is discussed with emphasis on stability considerations. Real-time system control has only recently been considered as applicable to stability, using conventional control methods. The report considers the use of artificial neural networks to improve the stability of the power system. The networks are considered as adjuncts and as replacements for existing controllers. The optimal kind of network to use as an adjunct to a generator exciter is discussed.

FOREWORD

THIS REPORT discusses the application of the relatively new technology of artificial neural networks to one of the oldest problems of electric power systems: stability. Power systems are nonlinear in certain respects, and that means that instability of various kinds is possible. The instability considered in this report is the kind demonstrated in the New York blackout of 1965.

While the problem is an old one, it is likely to be of increasing importance to find a solution. A number of evolutionary pressures are acting now so as to change radically the nature of the industry. These were reviewed at a meeting organized by the Department of Energy in Denver, CO, in March 1990. Real-time control and operation was considered in detail at a DOE Workshop, also in Denver, in November 1991. At the first meeting, the factors affecting the evolution of the industry were thought to include

- the regulatory process
- industry competitiveness
- new technologies
- load growth
- renewable sources and storage
- environmental concerns

Because of the first 3 of these factors, it was estimated that by 2020 over 50% of new generation would be non-utility owned, and transmission line loading would be high. These are the ingredients for trouble. The report of the first Denver meeting concluded that blackouts and brownouts would occur if present control devices and operating practices continued to be used.

The work described in this report is aimed at developing new control devices and operating practices that may contribute to forestalling the difficulties seen for the future power system. Given the lead-time required to put any new technology into practice, it is not too early to start investigating such advanced concepts as controllers based on artificial neural networks. Our work shows that neural nets could be a valuable addition to the options available for power system operation.

Because we are mixing two disparate technologies, power systems and neural nets, some background material on both topics is included in this report. The reader who feels the need to brush up on either topic should find help in Part 1 or Part 2 of the report. The reader who is comfortable in both areas may skip directly to Part 3.

HAROLD KIRKHAM

PASADENA, CALIFORNIA
NOVEMBER 1991

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PART 1. POWER SYSTEM STABILITY

POWER SYSTEM OPERATION is a complex topic. The way energy flows in an interconnected network is not obvious, and difficult to analyze even in the steady state. The fact that the system is nonlinear can lead to instability. The objective of maintaining high reliability of service in spite of these features of the system have led, over the years, to some conservative ways of operating.

It seems fair to ask why the electric power system presents a problem in determining load flow. After all, the components of the power system, the lines, transformers and generators are all well-understood devices. In part the difficulty stems from the fact that the load on the system is not known. It can be said that the load is not simply resistive, and is distributed geographically, but its power demand is not known, or indeed directly measurable. Another part of the problem arises from the way the system parameters are specified. An example will illustrate the point.

Consider the simple system shown in Figure 1-1. There are two generators, a single load, and two resistors representing the losses in the transmission lines. Although most power systems are ac, we can demonstrate the analytical difficulties with a dc system, as shown.

We begin by specifying that the left generator output is 100 W, and the load power is 150 W at 100 V. (This kind of specification of the generation is reasonably representative of power system practice. The left generator might be a small efficient unit, running at full power.)

The problem is to determine the bus voltages V_1 and V_2 and the power to be delivered by the right generator. When these three quantities are known, the system operating conditions will be known.

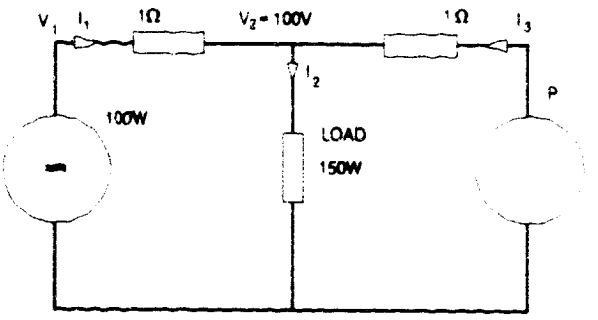


Figure 1-1.
Simple power system

The load current is

$$I_2 = \frac{150\,\mathrm{W}}{100\,\mathrm{V}} = 1.5\,\mathrm{A} \tag{1-1}$$

Two expressions can be written for I_1:

$$I_1 = \frac{100}{V_1} \tag{1-2}$$

and

$$I_1 = \frac{V_1 - V_2}{1} \tag{1-3}$$

from which $I_1 = V_1 - 100$.
The voltage V_1 of the left generator is uniquely specified because

$$\frac{100}{V_1} = V_1 - 100 \tag{1-4}$$

or

$$V_1^2 - 100\,V_1 - 100 = 0 \tag{1-5}$$

This may be solved directly

$$V_1 = 100.99\,\mathrm{V} \tag{1-6}$$

Of course,

$$I_1 = \frac{100}{V_1} = 0.99\,\mathrm{A} \tag{1-7}$$

By Kirchoff's Current Law,

$$I_2 = I_1 + I_3 \tag{1-8}$$

and we can solve for I_3:

$$I_3 = I_2 - I_1 = 1.50 - 0.99 = 0.51\,\mathrm{A} \tag{1-9}$$

V_3 can be found by considering the volt-drop due to I_3 in the 1 Ω line resistance. The result is $V_3 \approx 100.51$ V. Now the power from the right generator can be found:

$$P_r = V_3 I_3 = 51.26\,\mathrm{W} \tag{1-10}$$

The system is now completely analyzed. The right generator must burn enough fuel to generate 51.26 Watts, and the field current must be adjusted for a terminal voltage of 100.51 V. The left generator must supply 100 W at 100.99 V.

Although the system is extremely simple, the above analysis illustrates some important concepts. In the real world, the exact power of the load is not generally known. In scheduling the generation, one generator is designated as the "slack" machine (the right hand generator in the example), characterized by an initially unknown power generation. The power is then adjusted so that the frequency is at the required value: by definition the demand is then being met.

The purpose of a load flow calculation such as the one above is to determine the voltages and power flows throughout the system, based on the measured data. There are 5 degrees of freedom in the circuit of Figure 1-1. In other words, the specification of five independent quantities serves to totally determine the behavior of the system. In our example, the five quantities were the power of the left generator, the power of the load, the load voltage and the two line resistances. These are not the traditionally specified parameters. The load is geographically distributed, and is voltage dependent. Load power is therefore not known, but must be found in a load flow calculation.

The specification of different parameters has a profound effect on the calculation. Let us solve the system again with the following parameters specified: the power of the left generator, the two line resistances, the power at the load and the voltage at the right generator. This system is shown in Figure 1-2.

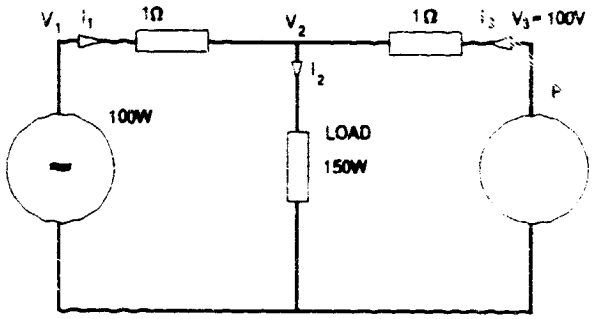


Figure 1-2.
Respecified system

We proceed in a straightforward fashion to determine the power to be supplied by the right generator as well as the two remaining bus voltages V_1 and V_2.

$$I_3 = \frac{P}{100} \tag{1-11}$$

$$V_2 = 100 - 1I_3 = 100 - \frac{P}{100} \tag{1-12}$$

$$P_{load} = V_2 I_2 = 150 \tag{1-13}$$

$$I_2 = \frac{150}{\left[100 - \frac{P}{100}\right]} \tag{1-14}$$

$$I_1 = I_2 - I_3 = \frac{150}{\left(100 - \frac{P}{100}\right)} - \frac{P}{100} \tag{1-15}$$

$$\begin{aligned} V_1 &= V_2 + 1 I_1 \\ &= \left(100 - \frac{P}{100}\right) + \frac{150}{\left(100 - \frac{P}{100}\right)} - \frac{P}{100} \end{aligned} \tag{1-16}$$

$$P_{\text{left}} = 100 = V_1 I_1 \tag{1-17}$$

Substituting for V_1, I_1 in this equation yields one equation involving P that we can use to determine system operating point. The equation is a fourth order polynomial in P. Numerical evaluation leads to

$$P = 51.25\,\text{W} \tag{1-18}$$

The other values follow immediately:

$$I_3 = 0.5125\,\text{A} \tag{1-19}$$

$$\begin{aligned} V_2 &= 99.4875\,\text{V}, \quad I_2 = 1.5077\,\text{A} \\ V_1 &= 100.4827\,\text{A}, \quad I_1 = 0.9952\,\text{A} \end{aligned} \tag{1-20}$$

The analytic complexity of the solution is masked by the few lines above indicating that the equation is a fourth order polynomial in P. Although this second problem appears to be a minor variation of the first (indeed the final values for the current, voltage and power are not significantly different), the mathematical complexity is such as to require numerical techniques. And this is for a system with only five degrees of freedom! A real power system will have several thousand degrees of freedom, and will be specified in the way our second example was specified. Numerical methods are clearly called for.

We have seen how difficult it is to fix the steady-state operating point of a power system. Now let us turn to the dynamics of the system.

Once more, we will illustrate the problem by means of an example. Consider another simple power system, consisting of one machine and an infinite bus[1], connected by two transmission lines, as shown in Figure 1-3.

[1] An infinite bus is a hypothetical convenience. It is a connection point defined so that whatever power is inserted into it (or taken out of it), the frequency and the voltage remain constant. This has the advantage for our purposes that it makes the equations of motion of the system much simpler. (In practice, as far as any single generator in a power system is concerned, the remainder of the system looks very much like an infinite bus. Choosing to use an infinite bus in the following example is not much of an approximation.)

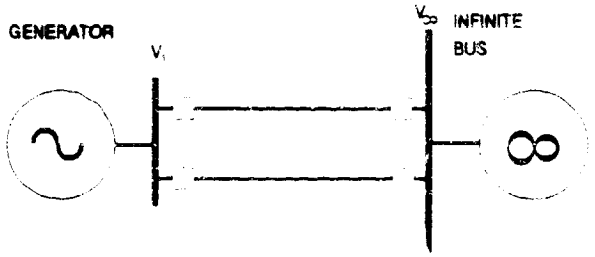


Figure 1-3.
Machine and infinite bus

Note that this diagram uses a different representation for the power system. This representation is a *single line diagram*, often used when the concern is more with the flow of power than the details of the circuit, as we are here. The three-phase lines and buses are shown simply as lines, and the machines as circles. The square boxes represent circuit breakers.

The voltage at the terminals of the generator is V_1, and at the infinite bus is V_∞. If the impedance of the two transmission lines is X, the power flow into the infinite bus can be written

$$P = \frac{V_1 V_\infty}{X} \sin\delta \tag{1-21}$$

where δ is the angle between the voltage phasors V_1 and V_∞. The angle δ is called the power angle, because it is this parameter that primarily determines the power transfer, as will be seen below.

There are a number of simplifications in the preceding development. For instance, it is assumed that the value of the impedances (lumped together as the transfer impedance X between the generator and the infinite bus. In practice, this is not the case. The impedance includes a component that is due to the generator itself, chiefly the inductance of the generator windings. This impedance is not constant as the power output of the generator varies, because the position of the generator rotor with respect to the rotating field of the stator varies. Since part of the rotor has been machined to accommodate the windings, the inductance is not constant as a function of position.

Another assumption is that the generator voltage is constant, or rather that the voltage behind the impedance of the generator is constant. This is only true if there is no automatic voltage regulator (AVR) on the machine. In practice, AVRs are fitted to all machines, and using a model such as that shown in the Figure, the best simple approximation would be that V_1 is constant.

Nevertheless, the equation for the power transfer illustrates some important points. First, the power transfer does not depend on the voltage. V_∞ is constant by definition. V_1 is practically constant. The power transfer is primarily a function of the angle δ between the voltages at the two ends of the system.

Second, the power transfer is inversely proportional to the transfer impedance. If the impedance X is due to two identical lines of impedance $2X$, the loss of one line would instantly halve the power transfer. More about this in a moment.

Third, the power transfer has a maximum value given by $(V_1\ V_\infty)/X$. If the voltage magnitudes are nominal, or 1 per unit, the maximum power transfer is simply $1/X$, and occurs when δ equals 90°.

It is this sinusoidal dependence on δ and the existence of a maximum value for the power transfer that makes the system capable of becoming unstable. Suppose that the machine is operated so that $\delta = 45°$ when one of the transmission lines is tripped out. If the two lines are

identical, there will be a problem. Before the line is tripped we have

$$P_{transfer} = \frac{V_1 V_2}{X} \sin 45^\circ = \frac{0.707}{X} \tag{1-22}$$

In other words, the power transfer is approximately 70% of its maximum value for the system. After the line is removed, the maximum possible power transfer is halved. The generator finds that it is operating with too low a value of δ to transfer the input power. The excess power goes into accelerating the machine, which serves to increase δ.

In this particular case, when δ reaches 90° there is still an excess of input power over power transferred, and the machine continues to accelerate. The post-fault value of maximum power transfer is half the pre-fault value, and the input power is 70% of the pre-fault value, or 140% of the post-fault maximum. The machine continues accelerating indefinitely, and will eventually be tripped out. This kind of instability is called steady-state instability, because there is no steady-state solution to the problem.

The usual answer to this kind of problem is to avoid it by operating with a smaller power angle. This is a very conservative approach, and it means that equipment is being under-utilized. Of course, as the transmission system becomes more interconnected, the loss of a single line would not mean a doubling of the transfer impedance, so larger values of power angle can safely be used. However, there are still many instances where standard practice is to keep power angles at less than 30° during normal operation. In such a case, the stability question is determined by the dynamics of the system. The question of what is called transient stability arises.

We said above that the machine would accelerate when it was being driven with more power than was being transferred out electrically. The equation of motion is

$$M\frac{d^2\delta}{dt^2} + P_{max}\sin\delta = P_{out} \tag{1-23}$$

where M is the inertia constant of the machine, and P_{max} is the maximum power that could be transferred, V_1V_2/X. If δ is constant, the first term vanishes and the equation restates the sinusoidal nature of the power transfer equation. When the value of δ is changing, the motion is similar to that of a pendulum, governed by a second-order nonlinear equation. The equation of motion is called the swing equation.

Note that there is no first order term in the swing equation. This means that the motion is undamped. Once an oscillation is started, there is nothing to prevent its continuing indefinitely. This is because the resistance terms in the power system (line losses and the like) are negligible in effect. In the derivation of the swing equation (which can be found in the text books, for example Kimbark, *** or Stevenson, ****), the resistances are explicitly ignored. In practical terms, this is a good, perhaps conservative, approximation. In a large, interconnected system with many generators, there are so many other factors that can affect the motion of a generator (particularly exciter control systems) that the damping is usually very small.

Suppose that, for some unspecified reason, one line in the system of Figure 1-3 trips out. In terms of the power-angle curves, the result is as shown in Figure 1-4.

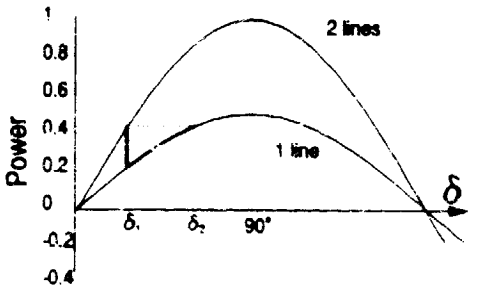


Figure 1-4.
Power-angle curve

Before the fault, the system is operating with power angle δ_1. After the line has tripped, operation at the same power level (about 0.4 per unit) could resume at power angle δ_2, as shown by the dotted line. However, the system trajectory is actually as shown by the heavy line in the Figure. At first, the power angle does not change. The power decreases (to less than 0.2 per unit). The excess input power accelerates the machine, and the power angle increases towards δ_2.

Although the heavy line in the Figure stops at δ_2, in practice the momentum of the system will cause an overshoot beyond the new steady-state operating point. If the power angle increases beyond 90°, further increases in power angle will result in a decrease in power transferred, and the system will be unstable. This could happen because of the overshoot. The system shown would exhibit transient instability. It is precisely this kind of instability that the work applying artificial neural nets, described in the third part of this report, is designed to prevent.

There are several simplifying assumptions behind this discussion. Most importantly, it has been assumed that the excitation is constant. If, instead, the excitation is made a function of the power angle, the power angle curve can be modified so that increased power can be transferred, at the cost of increasing the voltage in the system. In the real world, a generator is usually connected to an interconnected network of other machines, and there is no single value of δ. The excitation may be varied according to a locally available measurement, such as the derivative of the machine speed. This has the effect of adding a derivative term to the equation of motion, and improving the stability by adding damping. (It may also have the unwanted effect of resonating with system parameters, but that need not concern us here.) The device that is used to modulate the excitation for this purpose is termed a power system stabilizer.

The use of an artificial neural network as an adjunct to or a replacement for a power system stabilizer to modulate the excitation is the subject of the third section of this report. In the next section, we introduce the topic of artificial neural networks, as background for this application.

PART 2: NEURAL NETWORKS

THE QUEST for efficient computational approaches to artificial intelligence (AI) has undergone a significant evolution in the last few years. Attention has come to focus on the application of neural learning concepts to some of the many tasks performed by machines. This must be complemented by some insight into how to combine symbolic reasoning with massively parallel processing abilities. Computer scientists seek to understand the computational potential of this emerging technology. They are interested in knowing the fundamental limitations and capabilities of handling unstructured problems by intelligent machines. Issues such as this are central to the deeper question of the feasibility of neural learning *vis à vis* artificial intelligence.

The focus of this part of the report is narrower; to examine generally the capabilities of neural network learning. Machine learning in the context of neural networks is examined from the standpoints of computational complexity and algorithmic information theory.

Not only is the concept of massively parallel neuroprocessing of scientific interest, it is also of great practical interest. It is changing the nature of information processing and problem solving. In general, the scientific and engineering community is faced with two basic categories of problems. First, there are problems that are clearly defined and deterministic and controllable. These can be handled by computers employing rigorous, precise logic, algorithms, or production rules. This class deals with *structured problems* such as sorting, data processing, and automated assembly in a controlled workspace. Second, there are scenarios such as maintenance of nuclear plants, undersea mining, battle management, and repair of space satellites that lead to computa-

tional problems that are inherently ill-posed. Such *unstructured problems* present situations that may have received no prior treatment or thought. Decisions need to be made, based on information that is incomplete, often ambiguous, and plagued with imperfect or inexact knowledge. These cases involve the handling of large sets of competing constraints that can tolerate "close enough" solutions. The outcome depends on very many inputs and their statistical variations, and there is not a clear logical method for arriving at the answer. The focus of artificial intelligence and machine learning has been to understand and engineer systems that can address such unstructured computational problems.

Engineered intelligent systems, that is expert systems with some embedded reasoning, such as might be used for autonomous robots and rovers for space applications, behave with rigidity when compared to their biological counterparts. Biological systems are able to recognize objects or speech, to manipulate and adapt in an unstructured environment and to learn from experience. Engineered systems lack common sense knowledge and reasoning, and knowledge structures for recognizing complex patterns. They fail to recognize their own limitations and are insensitive to context. They are likely to give incorrect responses to queries that are outside the domains for which they are programmed. Algorithmic structuring fails to match biological computational machinery in taking sensory information and acting on it, especially when the sensors are bombarded by a range of different, and in some cases competing, stimuli. Biological machinery is capable of providing satisfactory solutions to such ill-structured problems with remarkable ease and flexibility.

An important part of any development for unstructured computation today is to understand how unstructured computations are interpreted, organized, and carried out by biological systems. The latter exhibit a spontaneous emergent ability that enables them to self-organize and to adapt their structure and function.[2]

Technical success in emulating some of the fundamental aspects of human intelligence has been limited. The limitation lies in the differences between the organization and structuring of knowledge, the dynamics of biological neuronal circuitry and its emulation using symbolic processing. For example, it has been said that analogy and reminding guide all our thought patterns, and that being attuned to vague resemblances is the hallmark of intelligence (Hofstader, 1979; Kanal and Tsao, 1986; Linkser, 1986a,b; Winograd, 1976). Thus, it would be naive to expect that logical manipulation of symbolic descriptions is an adequate tool. Furthermore, there is strong psychophysical evidence that while the beginner learns through rules, the expert discards such rules, somehow instead discriminating thousands of patterns, acquired through experience in his domain of expertise.

It is rapidly becoming evident that many of the unstructured problems, can be solved not

[2] A comment about the use of the word *emergent* is in order. The first dictionary definition is usually *emerging*, which doesn't help much. *Suddenly appearing* and *arising unexpectedly* are lower in the list of meanings. Almost certainly, the use of emergent in our context derives from the *emergent theory of evolution* which holds that completely new organisms or **modes of behavior** appear during the process of evolution as a result of unpredictable rearrangements of pre-existing elements. This use carries with it the notion that the results do not arise from a higher external control, but from the operation of a form of natural selection. In nature, the process occurs as a result of feedback, strengthening some (biological) neural connections and weakening others during learning. In our application, the natural selection corresponds to the adjustment of the weights during the training of the artificial neural network.

with traditional AI techniques, but by "analogy", "subsymbolic" or pattern matching techniques. Hence, *neural networks*, a biologically inspired computational and information processing approach, provides us with an inherently better tool. In the remainder of this report, we present tutorial material that will function as a background for further work on the application of artificial neural networks to power system problems. The remainder of this section of the report concentrates on neural networks. Their application to the control problems of power system stability is examined in Part 3. A mathematical formalism that can provide an enabling basis for solving complex problems is reserved for an Appendix.

The problem of interest here is one that has been addressed for the last several decades, namely, *functional synthesis*. Specifically, we focus on learning nonlinear mappings to abstract functional, statistical, logical and spatial invariants from representative examples. However, before we formally introduce neural networks in the technical core of this report, we present arguments comparing the suitability of neural networks and formal AI to solving problems in computational learning.

AI Modeling and Neural Networks

Over the last three decades, AI and neural network researchers have charted the ground in the areas of pattern recognition, adaptive machine learning, perception and sensory-motor control. This has provided an assessment of what is difficult and what is easy. Although both disciplines have similar goals, there is not much overlap between their projected capabilities. The basis of both approaches may be traced back to hypotheses of Leibniz (1951) and Weiner (1986). They identified humans as complicated goal-seeking machines, each composed of an "intelligent" brain and highly redundant motor systems. This machine can detect errors, change course, and adapt its behavior so that achievements of goals is more efficient.

Later development of intelligent systems has pursued two distinct schools of thought; *symbolic* and *neurobiology*, or *connectionist*. AI researchers concentrated on what the brain did irrespective of how it was accomplished biologically, while the connectionists focussed on how the brain worked. The following material is written by a connectionist.

Rooted in the "rationalist, reductionist tradition in philosophy," AI assumes there is a fundamental underlying formal representation and logic that mirrors all primitive objects, actions and relations. This view of the world has the necessary and sufficient means for general intelligent action. Newell and Simon (1976), are the most forceful proponents of this approach. They hypothesized that once such a representation were available, the operations of human cybernetic machinery could be fully automated and described by mathematical theorems and formal logic. They believed all knowledge could be formulated into rules. Hence, behavioral aspects of human reasoning and perception could be emulated by following rules or manipulating symbols, without regard to the varying interpretations of symbols. Further, in this view, intelligent behavior arises from the amalgamation of symbols in patterns that were not anticipated when the rules were written. Expert systems are product of such a line of investigation. However, as discussed by Reeke and Edelman (in Graubard, 1989), over the years AI researchers have struggled against fundamental systems engineering issues summarized as follows :

(a) **Coding Problem**: finding the suitable universal symbol system, ie the ultimate simple units by which all complex things can be understood;

(b) **Category Problem**: specifying a sufficient set of rules to define all possible categories and phenomena that the system might have to recognize;

(c) **Procedure Problem**: specifying in advance all actions that must be taken for all possible combinations of input;

(d) **Homunculus Problem**: This pins the fundamental problem of AI to the old puzzle of "infinite regress" in a universal symbol system. For example, when a person looks at an object, say a computer, how is the image of the computer registered in the brain ? All explanations hitherto proposed by AI attribute this process to some "intelligent device" inside the brain that is in charge of doing the registering. However, the same problem has to be faced again to explain how the "device" does the registering, and so on *ad infinitum*.

(e) **Developmental Problem**: devising mechanisms that can enable programmed systems exist: self-learn, self-organize their structure and function and self-replicate without explicit external manipulation, akin to adaptive biological systems;

(f) **Nonmonotonic Reasoning Problem**: designing rules that can function as retractable hypotheses, to mitigate the problems that arise when rules get executed without context-consistency checks.

Since formal AI has not been able to surmount the above problems using logical reasoning alone, some have suggested recourse to an alternate scientific paradigm—neural networks. In a radical philosophical departure from AI, the neural network community argues that logical reasoning is not the foundation on which cognition is based. Instead, cognition is an emergent behavior that results from observing a sufficient number of regularities in the world[3]. The theoretical underpinnings of this approach lie in biological detail and rigorous mathematical disciplines such as the theory of dynamical systems and statistical physics. Neural network theorists attempt to discover and validate the principles that make intelligence possible by observing existing intelligent systems, ie the brain. They hold the view that cognitive machinery is built from many simple, nonlinear, interacting elements. These neural networks store knowledge in their internal states and self-organize in response to their environments. Intelligent behavior results from collective interactions of these units.

Historically, the symbolic community has treated the human brain as a hierarchical system of components which obey the laws of physics and chemistry. The system could be described as the solutions to mathematical equations relating computable functions over the inputs and outputs of neurons. It is assumed that given an initial state and a sufficient amount of computing power, one could compute a person's next state. This approach ignored the framework of interpretation, "context-sensitivity," within which humans process information, make commitments and assume responsibility. The primary focus of AI became to design rule

[3] One might assume from the origin of the word that the *emergent* behavior is spontaneous in origin, and indeed this is the case. The inner workings of most networks defy exact comprehension. One should not, however, be too uncomfortable with this. Artificial neural networks are trained, and while the details of how that training actually functions cannot be precisely predicted, the overall result can be estimated satisfactorily.

systems that processed symbols without regard to their meanings. Thus, it completely ignored the considerable amount of subsymbolic or subconscious processing that precedes our conscious decision making, and later leads to the filtering of situations so that the appropriate rule may be used. In sharp contrast, rather than creating logical problem-solving procedures, neural network researchers use only an informal understanding of the desired behavior to construct computational architectures that can address the problem. This, it is hoped, will eliminate the fundamental AI limitation, lack of context sensitivity.

Whereas formal AI focusses on symbols, symbolic manipulation, or formal logic procedures, neural networks focus on association, units and patterns of activation. Neurocomputation primarily entails recognizing statistically emergent patterns, and processing alternatives obtained by relaxing various features that characterize a situation.

Therein lies the performance potential of neural networks. They are amenable to the development and application of human-made systems that can emulate neuronal information processing operations. Examples of applications include real-time high-performance pattern recognition, knowledge-processing for inexact knowledge domains, and precise sensory-motor control of robotic effectors. These are areas that computers and AI machines are not suited for. Neural networks are ideally suited for tasks where a holistic overview is required, eg to abstract relatively small amounts of significant information from large data streams, such as in speech recognition or language identification. On the other hand digital computers and AI are ideal for algorithmic, symbolic, logical and high precision numeric operations that neural networks are not suited for. The two fields complement each other in that they approach the same problems but from different perspectives.

So far, we have tried to describe the application and potential of neural networks. We now present a brief summary of their evolutionary history.

Artificial Neural Networks

The field of artificial neural networks has been revitalized by recent advances in the following three areas:

1 our understanding of anatomical and functional architecture; the chemical composition, electrical and organizational processes occurring in the brain and nervous system.

2 hardware technology and capability, leading to physical realizations of neural networks

3 new network architectures with collective computational properties such as time sequence retention, error correction and noise elimination, recognition, and generalization.

Development of detailed models of neural networks began with the work of McCulloch and Pitts (1943). Using logical elements they demonstrated that synchronous neural nets could perform all quantifiable processes, eg arithmetic, classification, and application of logical rules. Hebb (1949) demonstrated that repeated activation of one group of neurons by another through a particular synapse leads it to activate synchronously groups of neurons to which it is weakly connected, thereby organizing strongly connected assemblies. Neumann (in Grossberg 1987b),

injected the notion of redundancy in neurocomputing. He constructed networks which activated many neurons to do the job of one. Winograd and Cowan (1963), extended his work to introduce the notion of distributed representation. In this representation, each neuron partially represented many bits. The field was put on a firm mathematical basis by Rosenblatt (1962). He conjectured that intelligent behavior based on a physical representation was likely to be hard to formalize. According to his arguments, it was easier to make assumptions about a physical system and then investigate the system analytically to determine its behavior, than to describe the behavior and then design a physical system by techniques of logical synthesis. He engineered his ideas, in a feedforward network of McCulloch and Pitts neurons (1943), named perceptrons. He attempted to automate the procedure by which his network of neurons learned to discriminate patterns and respond appropriately. A detailed study of perceptrons led Minsky and Papert (1969) to strong criticism of the field. Thereafter, neural network receded into a long slump. However, as observed by Ladd (1985), Minsky was mistaken in interpreting or suggesting that simple perceptrons were at the heart of connectionism. Their analysis was not valid for systems that were more complex, including multilayered perceptrons and neurons with feedback.

The resurgence of the field is due to the more recent theoretical contributions by Kohonen (1977-1987), Grossberg (1987a,1987b), Amari (1972-1983), Carpenter (1987a,1987b), Hopfield (1982,1984), and Zak (1988-1990). Hopfield's illuminating contributions have extended the applicability of neural network techniques to the solution of complex combinatorial optimization problems (Hopfield and Tank 1985).

As shown in Fig. 2-1, artificial neural systems may be characterized as distributed computational system comprised of many processing units. Each processing element has connected to it several others in a directed graph of some configuration. They have been defined (Kohonen, 1988) as

> massively parallel, adaptive dynamical systems modeled on the general features of biological networks, that can carry out useful information processing by their state response to initial or continuous input. Such neural systems interact with the objects of the real world and its statistical characteristics in the same way as biological systems do.

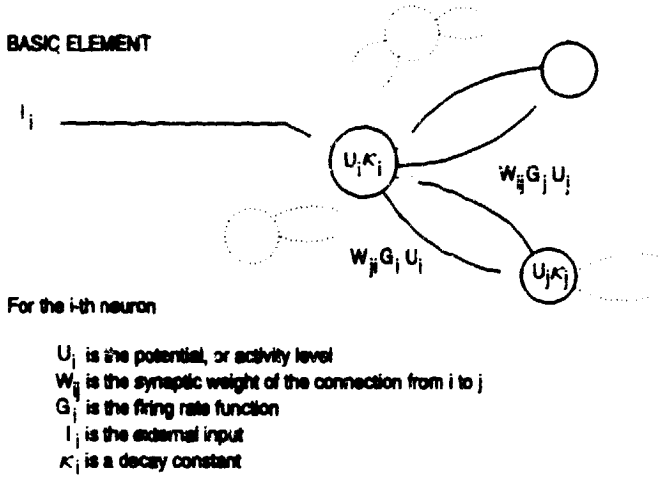


Figure 2-1.
Model of a neural system

Grossberg (1988) has observed that neural networks must:

(a) be nonlinear
(b) be nonlocal, ie exhibit long-range interactions across a network of locations.
(c) be nonstationary, ie interactions are reverabative or iterative.
(d) have nonconvex "energy-like" function.

The potential advantages of neuronal processing arise as a result of its ability to perform massively parallel, asynchronous and distributed information processing. Neurons with simple properties and interacting according to relatively simple rules can collectively accomplish complex functions.

Neural network modeling is a discipline which attempts to understand brain-like computational systems. It has been variously termed computational neuroscience, parallel distributed processing, and connectionism.

The bulk of neural network models can be classified into two categories; those that are intended as computational models of biological nervous systems or *neuro-biological models*, and those that are intended as biologically-inspired models of computational devices with technological applications, called *Artificial Neural Systems* (ANS).

Although our primary emphasis is on ANS, we will highlight the influence of neurobiology on the formulation of ANS models, and the resulting computational implications. To get a sense of the required size and interconnectivity of neuronal circuitry for intelligent behavior, we begin by examining biological neural networks. Most existing neural network models are based on idealizations of the biological neuron and the synaptic conduction mechanisms, shown in Figure 2-2.

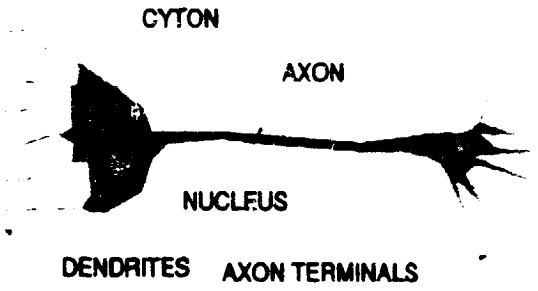


Figure 2-2.
Biological neuron

As shown in Fig 2-2, each neuron is characterized by a cell body or cyton and thin branching extensions called dendrites, that are axons specialized for inter-neuron transmission. The dendrite is a passive receiving and transmitting agent, whereas the axon is electrochemically charged, a highly active brain cell entity. The dendrites receive inputs from other neurons (by way of chemical neurotransmitters), and the axon provides outputs to other neurons. The neuron itself is imbedded in an aqueous solution of ions, and its selective permeability to these ions (the cell membrane contains ion channels) establishes a potential gradient responsible for transmitting information. The electrochemical input signals or the neurotransmitter is funnelled to the neuron from other neurons, to which it is connected through sites on the their surface, called synapses.

The input signals are combined in various ways, triggering the generation of an output signal by a special region near the cell body. However, the neurobiological phenomenon that is of particular interest is the changing chemistry of the synapse as information flows from one

neuron to another. The synapse instantaneously decides when the information is not essential and need not be resupplied. The weight of the individual charge is regarded as the determining factor. On the transmitting or pre-synaptic side of the synapse, triggering of the synaptic pulse releases a neurotransmitter that diffuses across a gap to the receiving side of the synapse. On the post-synaptic or receiving side, the neurotransmitter binds itself to receptor molecules, thereby affecting the ionic channels and changing the electrochemical potential.

The magnitude of this change is determined by many factors local to the synapse, eg the amount of neurotransmitter released, and the number of post-synaptic receptors. **Therefore, neurocomputation, biological self-organization, adaptive learning and other mental phenomena are largely manifested in changes in the effectiveness or "strength" of the synapses, and their topology**. Additional details on the biological neuron, membrane polarization chemistry and synaptic modification may be found in Aleksander (1989).

The above insights in neurobiology have led to the mathematical formulation of *simulated neurons*, ie the basic building block of neural network models. A functional model for a typical simulated neuron is shown in Figure 2-3.

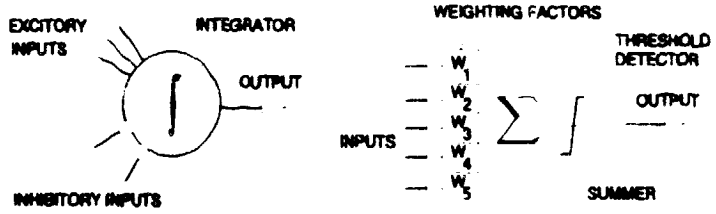


Figure 2-3.
Functional model of simulated neuron

Four useful areas may be abstracted. The first is the synapse where signals are passed from one neuron to another, and the amount of signal is regulated, ie gated or weighted by the strength of the synaptic interconnection. In the activated neuron region, called the *summer*, synaptic signals containing excitatory and inhibitory information are combined. This affects the tendency of a cell to fire or not. The threshold detector actually determines if the neuron is going to fire or not. The axonal paths conduct the output activation energy to other synapses to which the neuron is connected.

Useful properties such as generalization, classification, association, error correction, and time sequence retention emerge as collective properties of systems comprised of aggregations of many such simple units. When viewed individually, the dynamics of each neuron bears little resemblance to task being performed.

As discussed in the preceding paragraph, of particular computational and modeling interest are the mathematical notions of synapse and synaptic modification. Further attention is paid to mechanisms by which such units can be connected together to compute, and the rules whereby such interconnected systems could be made to learn.

Computational Neural Learning

The strength of neural networks for potential applications arises from their spontaneous (emergent) ability to achieve *functional synthesis*. That is to say, they learn nonlinear mappings, and abstract the spatial, functional or temporal invariances of these mappings. Relationships between multiple inputs and outputs can be established, based on a presentation of many

representative examples. Once the underlying invariances have been learned and encoded in the topology and strengths of the synaptic interconnections, the neural network can generalize to solve arbitrary problem instances. Applications which require solving intractable computational problems or adaptive modeling are of special interest.

Neural Learning has been defined as the process of adaptively evolving the internal parameters, eg connection weights and network topology, in response to stimuli (representative examples) being presented at the input (and possibly at the output) buffer. Neural networks modeled as adaptive dynamical systems relay on relaxation methods rather than heuristic approach for automatic learning.

Learning in neural networks may be *supervised*. In this case, the desired output response to the input stimuli patterns are obtained from a knowledgeable teacher. The network is presented with training patterns, and detect the statistical regularities embedded within them. It learns to exploit these regularities to draw conclusions when presented with a portion or a distorted version of the original pattern. The retrieval process involves presentation of one of the stimuli patterns, that have been repeatedly shown to the network during the training phase, to the network and comparison of the network response to the desired one. When a portion of a training pattern is used as a retrieval cue, the learned process is called *auto-associative*. When the presented input is different from any input presented during training then, learning is called *hetero-associative*.

When no desired output is shown to the network the learning is *unsupervised*. This kind of learning is relevant to grouping or clustering. For instance, let us assume that the network is presented with 10 different pictures of two different individuals. After training, the network will have three states, ie, individual A, B or not known. When the network is presented with one of the ten pictures, or a sufficiently close to one of them, it should converge to A or B. Presenting a totally new picture to the network, on the other hand, may result in convergence to either of the three states. However, to train the network on labeling the states is a task for supervised learning.

An intermediate kind of learning is *reinforcement learning*. Here, a teacher indicates whether the response to an input is good or bad, how far and in what direction the output differs from the desired output. The network is rewarded or penalized depending on the action it takes in response to each presented stimulus. The network configures itself to maximize the reward that it receives. To illustrate the point, let us take the analogy of a driver trying to park a car with the assistance of an outside person. In this case, the assistant, playing the roll of the teacher, will give only directions such as, left, more to the left, straight, etc. The teacher does not have the means to give quantitative value such as 20 degrees to the right. Once the training is done, the driver should be able to park the car without any assistant.

Along with the architecture, learning rules form the basis of categorizing different neural network models. A detailed description of different types of learning rules can be found in Lippmann (1987). Neural learning rules could take the following forms:

> *Correlational Learning*, where parameter changes occur on the basis of local or global information available to a single neuron. A good example is the Hebbian learning rule (Hebb, 1949), in which the connection weights are adjusted according to a correlation between the states of two interconnected neurons. If the two neurons were both active during some successful behavior, the connection would be strengthened to express the

positive correlation between them.

On the other hand, in *Error-corrected Learning*, the rules work by comparing the response to a given input pattern with the desired response. Weights modifications are calculated in the direction of decreasing error. Examples are the perceptron learning rule, and back-propagation. In this category, two methods are available for updating the weights: (a) add up the weight change due to all stimuli patterns and make an average, or (b) apply the weight changes due to each stimulus as they are computed. In principle, the two methods should converge into the same end results. However, simulation results indicate that the first approach be faster.

Another learning rule, *Reinforcement Learning* does not require a measure of the desired responses, either at the level of a single neuron or at the level of a network. Only a measure of the adequacy of the emitted response suffices. This reinforcement measure is used to guide the search process to maximize reward.

Another category is *Stochastic Learning*, where the network's neurons influencing each other through stochastic relaxation, eg, Boltzmann Machine. In this method, learning take place in two stages. First, the network is run with both the input and output neurons clamped (ie, the value of the input and output neurons set to desired values). Co-occurrencey probabilities are calculated after the network has reached a global minimum. This procedure is repeated with only the input neurons clamped. Synaptic weights are then adjusted according to gradient-descent direction.

Two important parameters that characterize the computational power of neural learning formalisms are the nature of the states of individual neurons, and the temporal nature of synaptic updating. The states of individual neurons may be either *discrete or continuous*. It has been shown that a network with a finite number of states is computationally equivalent to a finite state machine.

Further, the nature of time variable in neural computation may also be either discrete or continuous. In the discrete case, the dynamics can be modeled by difference approximations to differential equations. It has been shown that continuous time networks can resolve temporal behavior which is transparent in networks operating in discrete time. In all respects, the two classes are computationally equivalent.

Adaptive Neural Control System Architectures

In a fundamental sense, the control design problem is to find an appropriate functional mapping, from measured and desired plant outputs, to a control action that will produce satisfactory behavior in the closed-loop system. In other words, the problem is to choose a function (a *control law*) that achieves certain performance objectives when applied to the open-loop system. In turn, the solution to this problem may naturally involve other mappings, e.g. a mapping from the current plant operating condition to the parameters of a controller or local plant model, or a mapping from measured plant outputs to estimated plant state. Accordingly, a learning system that could be used to synthesize such mappings on-line would be an advantageous component of an intelligent control system. To successfully employ learning systems in this manner, one must have an effective means for their implementation and incorporation into the overall control system architecture.

Neurocontrol is defined as the use of well-specified neural networks to emit actual control signals. In the last few years, hundreds of papers have been published on neurocontrol, but virtually all of them are still based on five basic design approaches:

(1) Supervised control, where neural nets are trained on a database that contains the "correct" control signals to use in sample situations

(2) Direct inverse control, where neural nets directly learn the mapping from desired trajectories to the control signals which yield these trajectories

(3) Neural adaptive control, where neural nets are used instead of linear mappings in standard adaptive control

(4) The backpropagation of performance, which maximizes some measure of performance over time, but cannot efficiently account for noise and cannot provide real-time learning for very large problems

(5) Adaptive critic methods, which may be defined as methods that approximate dynamic programming (ie, approximate optimal control over time in noisy, non-linear environments)

Based upon preliminary studies, it is clear that methods 1, 2, 4 are not well suited to solve the problem at hand. At this stage, it also seems that both methods 3 and 5 are capable of solving the problem. However, an in-depth study is needed to demonstrate the superiority of one compared to the other. Since the neural adaptive control methodology has the advantage of being implemented in a straightforward manner, ie as an add-on to the existing adaptive controller, its implementation and performance will be investigated and analyzed first.

Having motivated by the basic features of neural learning systems for control, we will briefly describe hybrid control system architectures that exhibit both adaptive and learning behaviors. These hybrid structures incorporate adaptation and learning in a synergistic manner. In such schemes, an adaptive system is coupled with a neural learning system to provide real-time adaptation to novel situations and time-varying dynamics. The adaptive control system reacts to discrepancies between the desired and observed behaviors of the plant, to maintain the requisite closed-loop system performance. These discrepancies may arise from time-varying

dynamics, disturbances or unmodeled dynamics. The phenomena of time-varying dynamics and disturbances are usually handled through feedback in the adaptive system. In contrast, the effects of some unmodeled dynamics can be predicted from previous experience. This is the task given to the learning system. Initially, all unmodeled behavior is handled by the adaptive system; eventually however, the learning system is able to *anticipate* previously experienced, yet initially unmodeled behavior. Thus, the adaptive system can concentrate on novel situations (where little or no learning has occurred) and time-varying behavior.

In the following, two general hybrid architectures are outlined. The discussion of these architectures parallels the usual presentation of direct and indirect adaptive control strategies. In each approach, the learning system is used to alleviate the burden on the adaptive controller of continually reacting to predictable state-space dependencies in the dynamical behavior of the plant. Note that various technical issues must be addressed to guarantee the successful implementation of these approaches. For example, to ensure both the stability and robustness of the closed-loop system (which includes both the adaptive and learning systems, as well as the plant), one must address issues related to controllability and observability; the effects of noise, disturbances, model-order errors, and other uncertainties; parameter convergence, sufficiency of excitation, and nonstationarity; computational requirements, time-delays, and the effects of finite precision arithmetic. Many (if not all) of these issues arise in the implementation of traditional adaptive control systems; as such, there are some existing sources one may refer to in the hope of addressing these issues. Although these topics are well beyond the scope of this document, in some instances, the learning augmented approach appears to offer operational advantages over the corresponding adaptive approach (with respect to such implementation issues). For example, a typical adaptive system would require *persistent* excitation to ensure the generation of accurate control or model parameters, under varying plant-operating conditions. A learning system, however, would only require *sufficient* excitation, during some training phase, to allow the stationary, state-space dependencies of the parameters to be captures.

Direct Implementation

In the typical direct adaptive control approach, see Figure 2-5, each control action $\mathbf{u}$ is generated based on the measured $\mathbf{y}_m$ and desired $\mathbf{y}_d$ plant outputs, internal state of the controller, and estimates of the pertinent control law parameters $\mathbf{k}$. The estimates of the control law parameters are adjusted, at each time-step, based on the error $\mathbf{e}$ between the measured plant outputs and the outputs of a reference system $\mathbf{y}_r$. Of course, care must be taken to ensure that the plant is actually capable of attaining the performance specified by the selected reference system. Direct adaptive control approaches do not rely upon an explicit plant model, and thus avoid the need to perform on-line system identification.

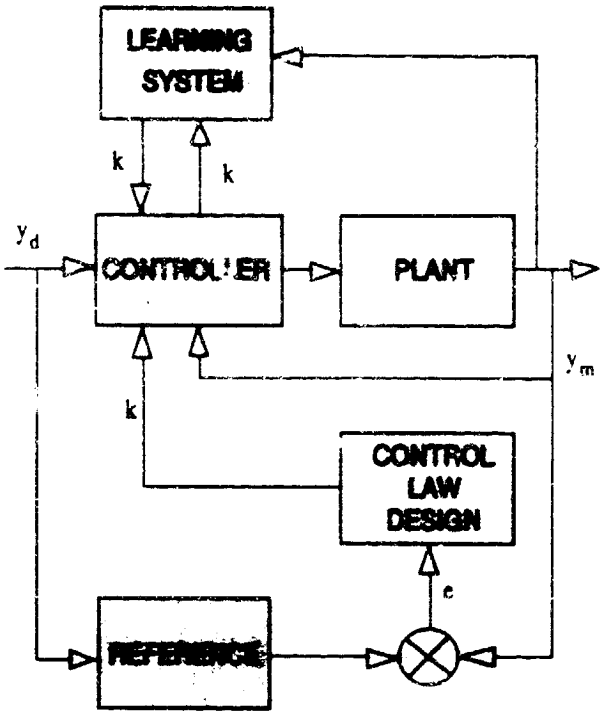


Figure 2-5.
Direct adaptive control

The controller in Figure 2-5 is structured so that normal adaptive operation would result if the learning system were not implemented. The reference represents the desired behavior for the augmented plant (controller plus plant), while the adaptive mechanism is used to transform the reference error directly into a correction, $\Delta \mathbf{k}$ for the current control system parameters. The adaptation algorithm can be developed and implemented in several different ways (eg, via gradient or Lyapunov-based techniques. Learning augmentation can be accomplished by using the learning system to store the required control system parameters as a function of the operating condition of the plant. Alternatively, learning can be used to store the appropriate control action as a function of the actual and desired plant outputs. The schematic architecture in Figure 2-5 shows the first case.

When the learning system is used to store the control system parameters as a function of the plant operating condition, the adaptive system would provide any required *perturbation* to the control parameters **k** generated by the learning system. The signal from control block to the learning system in Figure 1 is the perturbation in the control parameters $\delta \mathbf{k}$ to be associated with the previous operating condition. This association (incremental learning) process is used to combine the estimate from the adaptive system with the control parameters that have already been learned for that operating condition. At each sampling instant, the learning system generates an estimate of the control system parameters **k** associated with that operating condition, and then passes this estimate to the controller, where it is combined with the perturbation parameter estimates maintained by the adaptive system and used to generate the control action **u**. In the ideal limit where perfect learning has occurred, and there is an absence of noise, disturbances, and time-varying dynamics, the correct parameter values would always be supplied by the learning system, so that both the perturbations $\delta \mathbf{k}$ and corrections $\Delta \mathbf{k}$ generated by the adaptive system would become zero. Under more realistic assumptions, there would be some small degradation in performance because of adaptation (eg, $\delta \mathbf{k}$ and $\Delta \mathbf{k}$ might

not be zero because of noise).

In the case where the learning system is trained to store control action directly as a function of the actual and desired operating conditions of the plant, the adaptive system would provide any required perturbation to the control action generated by the learning system. Note that a dynamic mapping would have to be synthesized by the learning system if a dynamic feedback law were desired (which was not necessary in the first case). The advantage of this approach over the previous one is that a more general control law can be learned. The disadvantage is that additional memory is required and that a more difficult learning problem must be addressed.

Indirect Implementation

In the typical indirect adaptive control approach, see Figure 2-6, each control action **u** is generated based on the measured $\mathbf{y}_m$ and $\mathbf{y}_d$ desired plant outputs, internal state of the controller, and estimated parameters $\mathbf{p}_a$ of a local plant model. The parameters **k** for a local control law are explicitly designed on-line, based on the observed plant behavior. If the behavior of the plant changes (eg, because of nonlinearity), an estimator automatically updates its model of the plant as quickly as possible, based on the information available form the (generally noisy) output measurements. The indirect approach has the important advantage that powerful design methods (including optimal control techniques) may potentially be used on-line. Note, however, that computational requirements are usually greater for indirect approaches since both model identification and control law design are performed on-line.

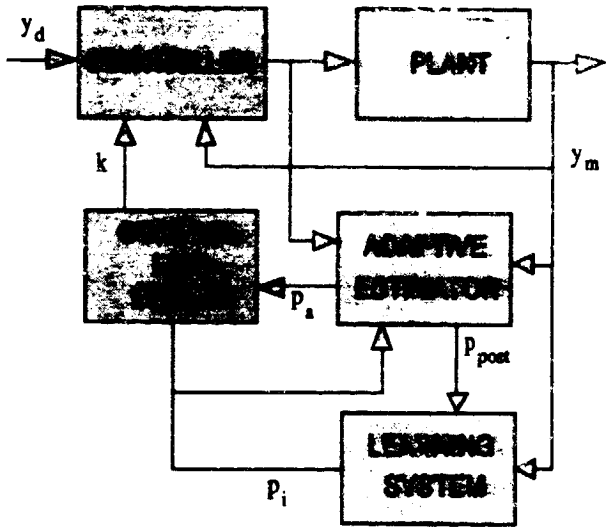


Figure 2-6.
Indirect adaptive control

If the learning system in Figure 2-6 were not implemented, then this structure would represent the operation of a traditional indirect adaptive control system. The signal $\mathbf{p}_a$ is the adaptive estimate of the plant model parameters. This signal is used to calculate the control law parameters **k**. Incorporation of the learning system would allow the plant model parameters to be learned as a function of the plant operating condition. The model parameters generated by the learning system allow previously experienced plant behavior to be *anticipated*, leading to improved control law design. In this case, the output of the learning system $\mathbf{p}_i$ to both the control

design block and the estimator is an *a priori* estimate of the model parameters associated with the current operating condition. And a *posteriori* parameter estimate $\mathbf{p}_{post}$ from the estimator (involving both filtering and posterior smoothing) is used to update the mapping stored by the learning system. The system uses model parameter estimates from both the adaptive and learning systems to execute the control law design and determine the appropriate control law parameters. In situations where the design procedure is complex and time-consuming, the control law parameters might also be stored (via a separate mapping in the learning system) as a function of the plant operating condition. Thus, control law design could be performed at a lower rate, assuming that the control parameter mapping maintained by the learning system was sufficiently accurate to provide reasonable control in lieu of design at a higher rate.

Summary

In both of the hybrid implementations described in this section, the learning system (prior to any on-line interaction) would only contain knowledge derived from the design model. During initial closed-loop operation, the adaptive system would be used to accommodate any inadequacies in the *a priori* design knowledge. Subsequently, as experience with the actual plant was accumulated, the learning system would be used to anticipate the appropriate control or model parameters as a function of the current plant operating condition. The adaptive system would remain active to handle novel situations and limitations of the learning system (eg, finite accuracy). With perfect learning, but no noise, disturbances, or time-varying behavior in the plant, the contribution from the adaptive system would eventually become zero. In the presence of noise and disturbances, the contribution from the adaptive system would become small, but nonzero (depending on the hybrid scheme used, however, the *effect* of this contribution might be negligible). In the general case involving all of these effects, the hybrid control system should perform better than either subsystem individually. It can be seen that adaptation and learning are *complementary* behaviors, and that they can be used simultaneously (for purposes of automatic control) in a *synergistic* fashion.

Neural Hardware Implementation

Even to date, a majority of the work in the field of artificial neural networks consists of theory, modeling, and software simulations of the massively parallel architectures on conventional digital computers. However, to realize the promise of a high speed, inherently parallel neural network architectures must be implemented in parallel hardware. This way, many neurons can actually communicate and orchestrate their activities simultaneously.

The basic components of electronic neural net hardware are conceptually and functionally extremely simple. The neurons can be implemented as thresholding nonlinear amplifiers and the synapses as variable resistive connections between them. An artificial neural network therefore, consists of many simple processing elements, representing neurons, which interact among themselves through networks of weighted connections functioning as synapses. The computation performed by the network is determined by the synaptic weights or connection strengths. The state of the system is identified by the pattern of activity of the neurons. Given an initial activity

pattern, each neuron receives input signals from the neurons and adjusts its output accordingly over time. The system rapidly evolves into steady activity pattern which is then interpreted as a memory recall or as a solution to a problem.

The field of neural networks, as might be expected, has developed its own computational terms. Some understanding of them is necessary to appreciate neural network simulation and implementation requirements. Some of the key concepts and terms are:

- o A typical neural network contains many more interconnects than neurons, or processing elements.
- o Each interconnect requires one multiply/accumulate operation for summing.
- o Digital computers are normally assessed in terms of storage or memory (where the unit of measure is words) and speed (instructions-per-second or floating-point-operations-per-second). The field of neural network defines **storage** as *the value of the input weights* and measures it by the *interconnects-per-second* within a layer or between layers. (This way of conceiving neural network storage is important only in the case of network simulation; in the case of implementation in special-purpose hardware, storage would be handled by resistive networks and would be defined differently.)

To understand this vernacular and its implications, we will use the terms *interconnects* and *interconnects-per-second* to chart a set of coordinates. We will place interconnects on the horizontal and interconnects-per-second on the vertical axis, respectively. The environment defined by this chart will be used to describe the computational capabilities of neural network systems and applications.

To fix the idea, let us introduce the computational capabilities of certain biological systems, as can be seen in Figure 5.

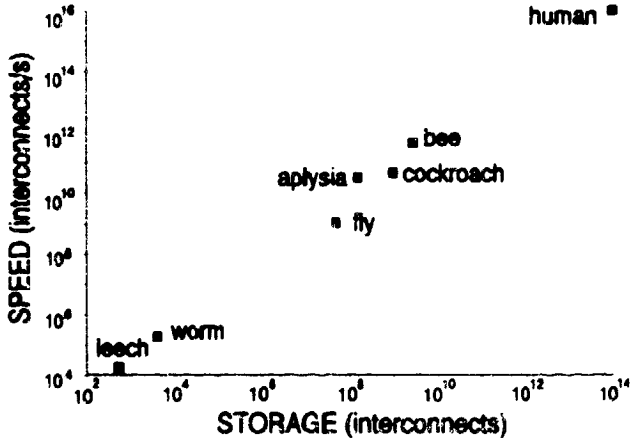


Figure 2-5.
Computational capabilities
of some biological systems

A human, with the staggering capacity of 10^{14} interconnects and 10^{16} interconnects per second, can be viewed as a superpower compared to creatures such as the worm, the fly, and the bee. In this context, neural network researchers would be very pleased to be able to replicate the computational capabilities of a fly or a bee with a machine. However, that will be difficult with the tools presently available. Today's neural network researchers have access to a variety of

digital tools, that range from low-priced microprocessor-based workstations, through attached processors and bus-oriented processors, to the more expensive massively-parallel machines, and finally to supercomputers.

Generally, the micro/minicomputers provide a very modest interconnects-per-second capability, though in some cases storage capacity is substantial. The speeds of these devices are limiting; neural network models take a very long time to run on them. Attached processors improve this situation somewhat, since they can boost interconnects-per-second into the millions from the hundreds of thousands. Bus-oriented processors, in some cases, raise by an order of magnitude the number of interconnects-per-second available, but storage is not equivalently greater. The massively parallel systems feature no better speed, and there remain gaps between their speed and storage capabilities. Supercomputers, meanwhile, do not offer significantly more capability than systems which cost far less. In addition, the programming necessary to run neural network models on these massively parallel machines is very complex. It is, in fact, a problem which limits the extent to which these systems can be used to conduct neural network research. Moreover, the architectural limitations of these systems prevent researchers from stacking up several of them to significantly boost their storage or speed.

The present state of neural hardware, in the context of interconnects (storage) and interconnects-per-second (speed), may satisfy small size simulations. However, it is not very user-friendly for research, statistical work, or development of large databases. Nevertheless, several technologies are posed to push hardware capabilities beyond their present speed and storage limits:

- Gallium arsenide (GaAs) and special-purpose charge-coupled devices (CCDs) will push up the ceiling on interconnects-per-second.

- Continued developments in random-access memory (RAM) technology as well as the lesser-developed three-dimensional (3-D) chip technology are expected to expand current storage capacities.

- Multiprocessing, meanwhile, will allow the boundaries of simulation to be moved upward by an order of magnitude.

Certainly, if neural networks are to offer solutions to important problems, those solutions must be implemented in a form that exploits the physical advantages offered by neural networks. The advantages include high throughput that results from massive parallelism (realtime operation), small size, and low power consumption. In the near term, smaller neural networks may be digitally implemented using conventional integrated circuit techniques. However, in the longer term, implementation of neural networks will have to rely on new technologies. Currently, the developments of neural hardware are focused on the following three major areas:

- Direct VLSI/VHSIC (very large scale integration/very high speed integrated circuits). A mature technology limited to a low density of interconnects due to its two-dimensional nature. All the weights in a neural network implemented in direct VLSI/VHSIC would have to be stored in memory, which would consume a lot of capacity.

- Analog VLSI, which holds promise for a near-term solution. It is, also, two-dimensional and offers a high density of interconnects. This is accomplished, because the weights can be implemented in resistors, thereby obviating the need for additional memory.

- Optical technology, a less developed and longer-term than the silicon-based approaches and limited in the types of neural networks that it can implement. This offers a very high density of interconnects due to its three-dimensional nature.

Table 1 summarizes the state of the art neural hardware currently available or under further development. These new chips are needed not only to build neural network simulators, but also because they may become very valuable individually in neural network-based applications.

Table 1. Comparison of architectures and technologies

System	Accuracy (bits)	Speed μs/conn	Technology
Analog			
CMOS			
ANNA (AT&T)	6	1	0.9μ CMOS
Duong *et al* (JPL)	6	0.5	2μ CMOS
Kub *et al* (NRL)	6	0.5	3μ CMOS
CCDs			
Chaing (MIT)	6	0.6	3μ CCD
Optoelectronic			
Frye *et al* (AT&T)	6	0.5	Si:H
Digital			
Uchimuri *et al* (UNM)	8	0.1	0.8μ CMOS
Newell *et al* (NTT)	8	0.025	1.6μ CMOS
CID (Caltech)	6	0.6	2μ CMOS

The fabrication and investigation of neural network architectures with different levels of complexity and various sizes is currently the subject of research. Our approach, here at JPL, involves development of fully parallel, cascadable "building blocks". This effort has already resulted in neural hardware such as fully programmable synaptic interconnection arrays and nonlinear analog (variable gain sigmoid) neuron arrays. The modular building blocks have served very well as flexible and versatile research tools. These tools have been employed in study of the emergent properties of neural networks. They also provided a sound baseline and guidelines for designs and implementations of application-specific, high performance "neuroprocessors". Such neural hardware has successfully been used for solution of real-life problems, not only at JPL but also at several other institutions engaged in neural network research and development.

We have implemented both feedback and feedforward architectures using the cascadable synaptic and neuron building blocks. The computing speed of such systems exceeds 10^9 analog operations per second. This is an order of magnitude higher than speeds achievable by neural net simulations on sequential machines. Using these networks, we have demonstrated content-addressable, associative memory, terrain trafficability determination, and solutions to the color graph optimization and Hopfield-Tank traveling salesman problems. This work is currently leading to the development of application-specific neuroprocessors.

We, at JPL, have successfully demonstrated not only the feasibility of hardware implementations of neural networks, but also unique strengths of analog processing implemented in parallel hardware. This, in spite of its inherent, unavoidable precision limits and noise constraints.

Conclusions

1. Massively parallel information processing schemes, inspired by neural network models, have become a subject of great interest in recent years. Mathematical modeling and computer simulations have shown emergent computational properties of complex networks of neuron-like non-linear processing elements. These networks capture certain important aspects of intelligent information processing, not easily dealt with by existing digital and artificial intelligence (AI) technologies.

2 Neural network research has matured greatly, thanks to: (a)- development of advanced mathematical theories and new computer tools, and also (b)- a better understanding of neurobiology.

3. Artificial neural networks promise efficient solutions to a variety of problems such as associative, fault-tolerant, information processing, pattern recognition, control, and computation intensive global optimization operations. They also provide new capabilities, such as "learning" from experience in the field, self-organization, and generalization, to solve ill-posed problems.

4. Neural networks are an especially valuable technology when the availability of a good solution in a very short time is more important than its absolute accuracy.

5. A large portion of the work in the field, to date, is, however, primarily based on software simulation of the network architectures on standard sequential computers. Undoubtedly, a simulation of even a moderately large network, with a few hundred neurons, becomes a computation-intensive and time-consuming task on a sequential machine. To realize the potential speed in artificial, inherently parallel, neural network architectures, the neurons must process information in parallel.

6. Today's computer tools - with simulation capabilities of roughly 10^7 interconnects per second- fall far short of the computational capabilities of even modest biological networks; a fly, for instance, computes at 10^9 interconnects per second.

7. Under the sponsorship of ARPA, JPL has focused on the development and demonstration of feasibility of fully parallel neural network architectures. These are used as high speed research tools to study the emergent properties of neural networks.

8. Neural network technology readiness at JPL has already progressed from feasibility demonstrations to development and rapid hardware prototyping. Stand-alone application-specific algorithmic and coprocessor systems offering real-time functional capabilities, previously nonexistent, are now available. These tools offer orders-of-magnitude speed enhancement in computation intensive problems of interest.

PART 3. APPLICATION

THE OPERATION of an electric power system has two objectives: firstly security, secondly economic operation. First, it is necessary to ensure that there is enough generation and transmission capacity to meet the load. Then, if there is sufficient capacity, the most efficient way to meet that load can be sought. System operation can be viewed as controlling a multi-variable system within the constraints of secure operation. In a multidimensional space representation, the constraints are the boundaries of the space. The system operates at a point within (or on the boundary of) the space. More flexibility of operation would result from expanding the boundaries. Such additional flexibility would allow the freedom to improve efficiency. The object of the work in neural networks will facilitate energy efficiency pushing against the boundaries of secure operation.

In a power network, power flows will distribute themselves in the system according to Kirchoff's laws. The self-adjusting nature of the system means that the constraints that represent safe practice may be violated if part of the system changes (for example, because of a fault). This topic was reviewed in the first part of this report. The practical result is that the system must be carefully monitored and controlled.

Human operators, trained and experienced, are adept at operating even complicated power systems. This is the more impressive when one realizes the complexity and magnitude of the problem. However, no operator can control a system during a disturbance, or in the seconds following one. The actions of the operator are limited to ensuring that constraints are

not violated during normal operation, and to restoring as much of the system as possible, after a fault—and the ensuing actions of the protection system—have changed the system configuration. Nor can an operator cope with the swings that some systems experience because of devices that are installed to make possible the transmission of greater amounts of power over existing rights of way. The problem will be illustrated by means of the example of power system stabilizers.

The equations that govern the motion of a power system are second-order and non-linear. The fact that the equations are second order is of no great import, but the nonlinearity reflects the fact that the system can become unstable. Consider the system of Figure 3-1.

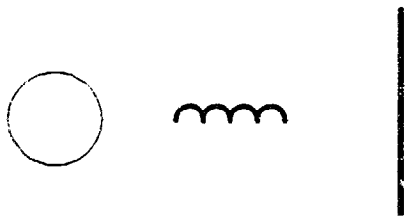


Figure 3-1.
Simple power system

For a simple power system, such as the one shown in Figure 3-1, consisting of only one generator and an infinite bus, the motion is described by the swing equation:

$$M\frac{d^2\delta}{dt^2} + P_{max}\sin\delta = P_{out}$$

where M is the inertia constant, a term related to the angular momentum of the generator, δ is the angle between the voltages V_1 and V_2 at the generator and the bus, X is the impedance of the generator, or more generally the impedance across which power is transferred, and P_{in} is the shaft input power.

Several simplifying assumptions have been made, particularly with regard to the constancy of the parameters. The angular momentum of the generator is a function of the speed. Clearly this is not constant during a swing. The generator impedance is not constant, either, since the rotor moves relative to the rotating magnetic field of the stator. It is also assumed that there is no exciter action, that is, the voltage behind the generator impedance is assumed constant. Nevertheless, in spite of these assumptions, the swing equation is instructive for the purposes of illustrating the behavior of the system.

This equation is basically a non-linear version of the equation that describes the motion of a pendulum. The oscillations typically have a frequency in the order of a second or so, determined by the inertia of the generator and the impedance of the generator and the line between the generator and the bus. The oscillations are not highly damped (there is no first-order term, because the resistances have been neglected), and can sometimes lead to instability.

The equation also shows that there is a maximum value to the amount of power that can be transmitted from the generator to the load. This occurs when δ reaches 90°. Any further increase in the power will result in instability.

In practice, systems with long lines are more prone to instability problems, because of the relatively large value of the transfer impedance. Some improvement can be made by adding capacitors in series with the line. However, this can affect the ability of the system to maintain a proper voltage profile, and can sometimes lead to subsynchronous oscillations (ie, oscillations

at frequencies less than power frequency), that can be damaging to generators. The instability problems are characterized by a frequency in the order of 1 Hz, a frequency which is much too fast for the generator governor to control. (Governor actuation involves moving a large, slow valve in the steam or water line driving the turbine.)

To guard against this kind of stability problem, it is possible to modulate the signal at the generator exciter. This is done by means of a control system called a power system stabilizer (PSS). In essence, a PSS functions by adding a derivative term to the equation of motion. It does this by modulating the exciter in response to changes in the power system. Power system stabilizers represent a relatively new technology, but one that may have its roots in some work done by the U.S. Bureau of Reclamation in the late 1960s [ref].

Figure 3-2 shows some of the control systems associated with a generator, including a power system stabilizer.

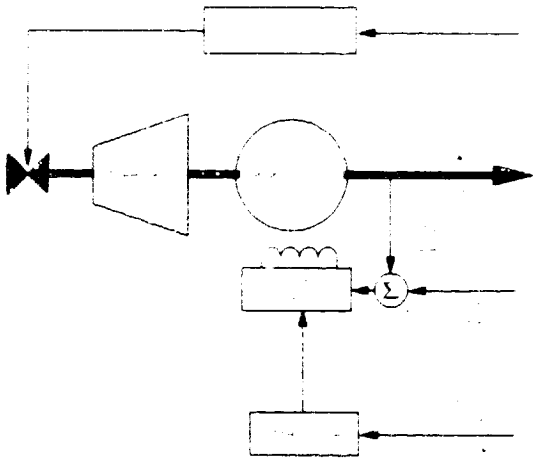


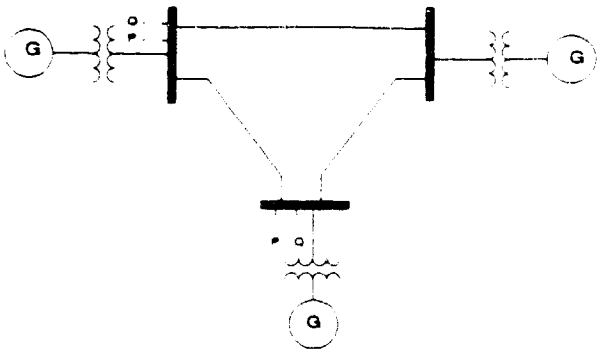
Figure 3-2.
Generator controls

For the application of a PSS to be successful, it must be "tuned" to the power system, that is, the parameters of the control system must be adjusted so that the modulation has the desired effect. Gains and frequency responses must be set to the appropriate values. Typically, a stabilizer will take the derivative of a speed signal, a process which is inherently noisy. To remove this noise, it will use a low-pass filter. Tuning thus becomes a problem of adjusting the lead and lag components of the filter in the stabilizer so that the appropriate correcting signal is available, without noise.

However, the parameters of the power system are not constant, being subject to daily, weekly and annual cycles, as well as the changes due to the occurrence and clearing of faults. PSS settings are rarely correct, therefore, long after the original settings have been made.

They suffer from another defect, too. When there is one machine and an infinite bus, it is easy to see in which direction the modulation must occur to improve the system stability. This is not so obvious when the power system becomes more complex. Consider the relatively simple 3-machine system of Figure 3-3.

Figure 3-3.
3-machine power system



In the Figure, three generators supply load to two buses. (One of the generators has no local load.) Suppose that a PSS is installed on one of the generators, and that the system is disturbed in some way. The PSS has been tuned for the situation shown, and will act so as to damp the swing of the machine to which it is attached. Note that the PSS tuning will not be correct if the system configuration changes. It is fortunate that PSS tuning is relatively "low Q."

Now suppose that a PSS is added to another generator. Interaction between the two control systems is inevitable. Just as a swing in one part of the system will affect the other parts of the system, so an action by a PSS in one part of the network will affect the other parts. This has not been a significant problem in the past because of the low penetration of PSSs into the power transmission system. However, power system stabilizers are increasingly likely to be seen as inexpensive alternatives to system reinforcements. Their impact on the power system will increase. Before long, PSS interactions will be a problem.

Application of neural networks

Artificial neural networks mimic the intelligent information processing abilities of the brain. This is accomplished through a massively parallel architecture containing a number of logic elements (the biological term is neurons, but the word node is sometimes used), connected to each other with variable strengths through a large network of interconnections (synapses).

Collectively, neurons with simple properties can accomplish complex functions such as control, pattern classification, information reconstruction, and learning. Their strength for many applications arises from their ability to learn and abstract spatial and/or temporal invariances of mappings. These networks can be built in hardware, or simulated in software.

A solution to the problems of power system stability control based on the use of artificial neural networks would have wide applicability; as well as being useful as adjuncts to power system stabilizers, they could be used for control in systems containing **dc links**, for example, and systems containing **FACTS** devices. (FACTS stands for flexible ac transmission system. The flexibility comes from the use of devices based on solid state switching to control the apparent value of system parameters by changing the relationship between voltage and current.)

Implemented as an adjunct to a power system stabilizer, a neural net solution might be as shown in Figure 3-4. Other forms of implementation are possible. In Figure 3-4 the neural network is essentially an add-on to the stabilizer. In a fully developed system, there may be no need for the stabilizer to exist separately from the neural network. All the functions of the stabilizer could be implemented in the network.

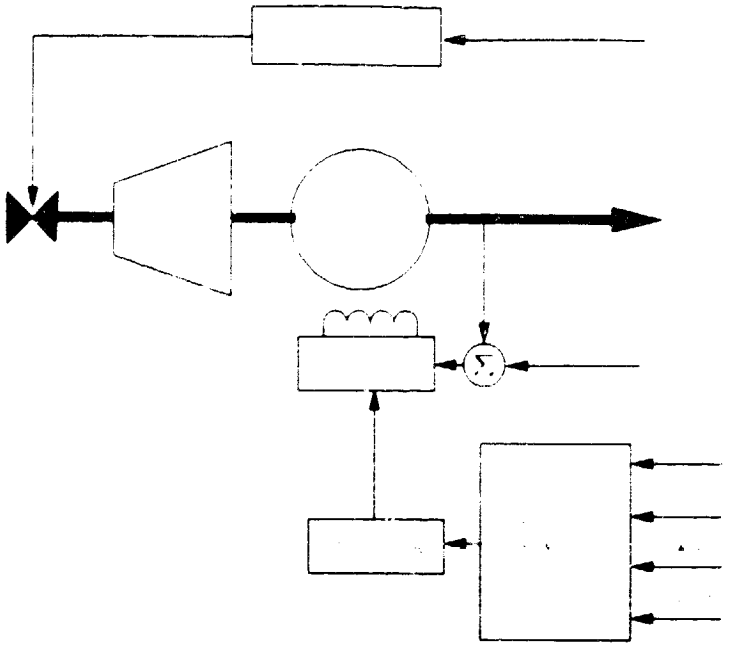


Figure 3-4.
Power system stabilizer with neural network

An advantage of the implementation shown in Figure ** is that the stabilizer works without the need to choose the input parameter (speed, frequency or power) in advance. The neural network can make this choice in real time, probably as some kind of optimal blend of parameters. The exact blend would depend on the particular system disturbance, so that the system performance should be better than a conventional stabilizer. Other advantages include the possibility of training the system off-line in advance of installation, and the ability of the stabilizing function to track system changes in the years that follow initial installation.

At present there are relatively few systems with dc links, and these tend to be large links installed primarily for the transfer of large amounts of power over long distances. A major example of this is the Pacific Intertie, an arrangement of two ac lines and one dc line that brings power from the predominantly hydro resources of the Pacific North-West to southern California. It is pointed out that the power flow on the dc line is modulated so as to improve the stability of the underlying ac system [ref].

If dc links become more common—and this is thought to be a thrust of other research being funded by DOE—interaction could be avoided simply by not modulating the power flow in response to conditions in the ac system. However, this would be failing to take advantage of an opportunity to use the system more efficiently, and the cost could be very large. Modulation should be considered from the outset. A complex system of multiple controllable dc links would be an ideal candidate for neural net operation.

FACTS devices were designed to be modulated. The paradigm is the variable capacitor, designed to be used in series with a long transmission line. The FACTS device would enable the apparent value of the line impedance to be modulated; essentially varying X in Figure **. It is understood how the modulation signal for a FACTS device should be derived. It is not understood what to do when there are multiple devices.

Task 1: Feasibility Study and Network Selection

The application of artificial neural networks to power system stability is motivated by the fact that neural networks are self-programmable computational tools. A net may be comprised of dozens or hundreds of simple processors that, like brain neurons, can receive and send signals to many others. The weights of the various connections (W_i in Figure 10) can be changed by training. The network changes its dynamic structure as a result of learning from its own "experience." One fascinating—and suggestive—aspect of neural nets is that their inner workings are not directly controlled, or even accessible. The network has "emergent" properties: that is it can exhibit new behavior by creating new combinations of pre-existing elements.

Various groups of AI researchers have concentrated on particular implementations of neural networks, and particular ways of training the nets. At the California Institute of Technology, an interconnected network that functions as a content-addressable memory was developed by Professor J.J. Hopfield. Weights are downloaded. Other multi-layer networks can be trained by "back-propagation," which functions much like negative feedback. A two-layer network first described by Professor T. Kohonen in 1982 is trained without supervision. The essential difference between the various networks is whether there are constraints on the permissible weights that, for example, prohibit or encourage lateral connection of neurons, or prohibit the backward flow of information in the network. For the time being, consider the neural network shown in Figure 11 to be a perfectly general network, in which any neuron is permitted a connection to any other.

Neural nets have much to offer over conventional computers. They can be faster and more robust, because of the parallel and distributed nature of the computation. They can also generalize, and respond accurately to situations that they have not seen before. It is this aspect of neural nets that makes them particularly attractive in many applications.

The work began in 1992, with a study of the feasibility of using neural nets to solve the problem of security assessment in power systems. While this study is not complete at the time of writing this Plan, the work has shown that the Kohonen net can indeed solve the security assessment problem. At present, a study is under way to examine the feasibility of using a neural network to perform active stability control. It can be assumed that neural nets will be shown to be a valid solution to the problem of the control of the large nonlinear power system. This being the case, the next step will be to build on this foundation by determining what kind of network offers most promise. Whatever the specific neural architecture finally selected for this particular application, the network can be made to learn to identify the behavior of the power system by changing the synaptic interconnections incrementally and recursively until all possible behaviors are learned. The trained neural networks will be tested and evaluated by presenting to it data from the training library as well as new data.

Task 2: Active Stability Control

By early 1994, the feasibility of using a neural net solution to address the problems of controlling the stability of the power system should have been demonstrated theoretically. The choice of which network type to use will likely also have been made. At this point, if it has not already been secured, industrial cofunding for the work will be sought. In collaboration with DOE and an industry co-sponsor, it will be decided whether a neural controller should be developed for FACTS devices, PSSs or for dc links.

Once the decision to address a particular subset of the problem is made, the proposed solution can be tested by simulation. This will certainly be a software simulation at first, and will require development of simulation code for the network and analysis software for the power system. At first, it will be appropriate to use a simplified model for the power system, consisting of a few buses and containing some simplifying assumptions. Once the neural network model has been shown to be capable of controlling such a system, a more complete model must be used.

A power system analysis package (such as PSS/U, written by Power Technologies Inc) would be an ideal candidate for a realistic test of the neural network solution. To perform such a test, the neural net simulation program and the power system transient stability program will have to be integrated, itself no trivial task.

A further step towards realizing neural net control of power system stability would be to implement the neural network in hardware, probably by means of a DSP approach, and to connect the hardware to a real power system. This work would require a careful, phased implementation approach, and it is unlikely it could begin until 1995 at the earliest.

Neural Learning Formalism

We formalize a neural network as an adaptive dynamical system whose temporal evolution is governed by the following set of coupled nonlinear differential equations:

$$\dot{u}_n + \kappa_n u_n = g_n\left(\gamma_n\left(\sum_m T_{mn} u_m + I_n\right)\right) \qquad t > 0 \tag{2-2}$$

where u_n represents the output of the n^{th} neuron, ($u_n(0)$ being the initial state). T_{nm} denotes the strength of the synaptic coupling from the m^{th} to the n^{th} neuron. The constants κ characterize the decay of neuron activities. The sigmoidal functions $g_n(\bullet)$ modulate the neural responses, with gain given by γ_n, typically, $g_n(x) = tanh(\gamma_n x)$. To implement a nonlinear functional mapping from an N_I-dimensional input space to an N_O-dimensional output space, the neural network is topographically partitioned into three mutually exclusive regions. As shown in Figure 2-4, the partition refers to a set of input neurons S_I, a set of output neurons S_O, and a set of "hidden" neurons S_H. Note that this architecture is not formulated in terms of "layers", and that each neuron may be connected to all others including itself. To specify the term I_n we distinguish between two different cases:

Figure 2-4.
Topology of a general network

Case 1: A temporal pattern is presented to the network. In which case, ***a(t)*** (henceforth the bold font will denote a vector) is a N-dimensional vector of target temporal patterns, with non zero elements, $a_n(t)$, in the input and output sets only. When trajectories, rather than mappings, are considered, components in the input set may also vanish. Hence, the time-dependent external input term in Eq. (1), ie $I_n(t)$, encodes component-contribution of the target temporal pattern via the expression

$$I_n(t) = \begin{cases} a_n(t) & \text{if } n \in S_I \\ 0 & \text{if } n \in S_H \cup S_O \end{cases} \tag{2-3}$$

To proceed formally with the development of a temporal learning algorithm, we consider an approach based upon the minimization of an error functional, E, defined over the time interval $[t_o, t_f]$ by the following expression

$$E(\boldsymbol{u},\boldsymbol{p}) = \frac{1}{2}\int_{t_o}^{t_f}\sum_n e_n^2 dt = \int_{t_o}^{t_f} F dt \tag{2-4}$$

where the error component, $e_n(t)$, represents the difference between the desired and actual value of the output neurons, ie

$$e_n(t) = \begin{cases} a_n(t) - u_n(t) & \text{if } n \in S_o \\ 0 & \text{if } n \in S_I \cup S_H \end{cases} \tag{2-5}$$

Case 2: Static patterns are presented to the network, in which case, the "source" term I_n^k, encodes contribution of the k^{th} training sample via the following expression

$$I_n^k = \begin{cases} I_n^k & \text{if } n \in S_I \\ 0 & \text{if } n \in S_H \cup S_o \end{cases} \tag{2-6}$$

As in the temporal case, the development of a static supervised learning algorithm, requires minimization of an error function, E, given by the following expression

$$E(\tilde{\boldsymbol{u}},\boldsymbol{p}) = \frac{1}{2}\sum_k \sum_n \left(\tilde{u}_n^k - a_n^k\right)^2 \quad \forall n \in S_I \cup S_o \tag{2-7}$$

Where vector $\tilde{u}$ denotes the steady state solution of the neural activation dynamics, Eq.(2-1).

In both static and temporal models, the internal dynamical parameters of interest are the strengths of the synaptic interconnections, T_{nm}, the characteristic decay constants, κ_n, and the gain parameters, γ_n. They can be presented as a vector of M ($M = N^2 + 2N$) components

$$\boldsymbol{p} = [T_{11}, \cdots, T_{NN}, \kappa_1, \cdots, \kappa_N, \gamma_1, \cdots, \gamma_N] \tag{2-8}$$

We will assume that elements of $\boldsymbol{p}$ are statistically independent. Furthermore, we will also assume that, for a specific choice of parameters and set of initial conditions, a unique solution of Eq. (2-1) exists. Hence, the state variables $\boldsymbol{u}$ are an implicit function of the parameters $\boldsymbol{p}$. In the rest of this document, we will denote the μ^{th} element of the vector $\boldsymbol{p}$ by p_μ ($\mu = 1, \cdots, M$) and limit ourselves to the temporal learning case due to its importance to our application.

Traditionally, learning algorithms are constructed by invoking Lyapunov stability arguments, ie by requiring that the error functional be monotonically decreasing during learning time, τ. This translates into

$$\frac{dE}{d\tau} = \sum_{\mu=1}^{M} \frac{dE}{dp_\mu} \cdot \frac{dp_\mu}{d\tau} < 0 \qquad (2\text{-}9)$$

One can always choose, with $\eta > 0$

$$\frac{dp_\mu}{d\tau} = -\eta \frac{dE}{dp_\mu} \qquad (2\text{-}10)$$

which implements learning in an inherently local minimization procedure. Attention should be paid to the fact that Eqs. (2-1) and (2-9) may operate on different time scales, with parameter adaptation occurring at a slower pace. Integrating the dynamical system, Eq.(2-9), over the interval $[\tau, \tau+\Delta\tau]$, one obtains

$$p_\mu(\tau+\Delta\tau) = p_\mu(\tau) - \eta \int_\tau^{\tau+\Delta\tau} \frac{dE}{dp_\mu} d\tau \qquad (2\text{-}11)$$

Equation (10) implies that, in order to update a system parameter p_μ, one must evaluate the *"sensitivity"* (ie, the gradient) of E, Eq. (3), with respect to p^μ in the interval $[\tau, \tau+\Delta\tau]$. Furthermore, using Eq. (3) and observing that the time integral and derivative with respect to p_μ commute, one can write

$$\frac{dE}{dp_\mu} = \int_{t_o}^{t_f} \frac{dF}{dp_\mu} dt = \int_{t_o}^{t_f} \frac{\partial F}{\partial p_\mu} dt + \int_{t_o}^{t_f} \frac{\partial F}{\partial u} \cdot \frac{\partial u}{\partial p_\mu} dt \qquad (2\text{-}12)$$

This sensitivity expression has two parts. The first term in the right hand side of Eq.(11) is called the "direct effect", and corresponds to the explicit dependence of the error functional on the system parameters. The second term in the right hand side of Eq. (11) is called the "indirect effect", and corresponds to the implicit relationship between the error functional and the system parameters via u. In our learning formalism, the error functional, as defined by Eq. (3), does not depend explicitly on the system parameters; therefore, the "direct effect" vanishes, ie

$$\frac{\partial F}{\partial p_\mu} = 0 \qquad (2\text{-}13)$$

Since F is known analytically (namely, Eqs. (3) and (4)), computation of $\partial F/\partial u$ is straightforward. Indeed

$$\frac{\partial F}{\partial u_n} = -e_n \qquad (2\text{-}13)$$

Thus, to enable evaluation of the error gradient using Eq. (11), the "indirect effect" matrix

$\partial u/\partial p$ should, in principle, be computed.

In summary, the problem of temporal learning is typically formulated as a minimization, over an arbitrary but finite interval, of an appropriate error functional. The gradients of the functional with respect to the various parameters of the neural architecture, eg synaptic weights, neural gains, etc. are essential elements of the minimization process. In the past, major efforts have been devoted to the efficacy of their computation.

Calculating the gradients of a system's output with respect to different parameters of the system is, in general, of relevance to several disciplines. Hence, a variety of methods have been proposed in the literature for computing such gradients. We will briefly mention only those which are relevant to our work.

Williams and Zipser (1989) presented a scheme in which the gradients of an error functional with respect to network parameters are calculated by direct differentiation of the neural activation dynamics. This approach is computationally very expensive and scales poorly to large systems. The inherent advantage of the scheme is the small storage capacity required, which scales as $O(N^3)$, where N denotes the size of the network.

Pearlmutter (1989), on the other hand, described a variational method which yields a set of linear ordinary differential equations for backpropagating the error through the system. These equations, however, need to be solved backwards in time. It requires temporal storage of variables from the network activation dynamics, thereby reducing the attractiveness of the algorithm.

Recently, Toomarian and Barhen (1992) suggested an approach for calculating the gradients of an error functional with respect to the system's parameters. It builds upon advances in nonlinear sensitivity theory. In particular, it exploits the concept of adjoint operators to reduce the computational costs. Two novel systems of equations for error propagation (ie, *the adjoint equations*), are at the heart of our computational framework. These equations are solved *simultaneously* (ie, forward in time) with the network dynamics. The computational complexity of the algorithm scales as $O(N^3)$ per time step. The storage requirements are minimal ie, of the order of $O(N^2)$.

References

Aleksander, I. (Ed.) (1989), *Neural Computing Architectures: The Design of Brain Like Machines*, Cambridge, MA: The MIT Press.

Amari, S. I. and M.A. Arbib (Eds.) (1982), *Competition and Cooperation in Neural Networks*, New York: Springer-Verlag.

Amari, S. I. (1979), "A Neural Theory of Association and Concept Formation", *Bio. Cyber.*, 26, 175 185.

Amari, S. I. (1972), "Characteristics of Random Nets of Analog Neuron-Like Elements", *IEEE Trans. Sys., Man, Cyber.*, SMC-2(5), 643-657.

Amari, S.-I. (1983), "Field Theory of Self-organizing Neural Networks", *IEEE Trans. Sys., Man, Cyber.*, SMC-13(5), 741-748.

Carpentar, G.A. and S. Grossberg (1987a), "A Massively Parallel Architecture for a Self-Organizing Neural Pattern Recognition Machine", *Comp. Vis., Gra., and Image Proc.*, 37, 54-115.

Carpentar, G.A. and S. Grossberg (1987b), "ART 2: Self-Organization of Stable Category Recognition Codes for Analog Input Patterns", *Applied Optics*, 26(23), 4919-4930.

Graubard, S.R. (1989), *The Artificial Intelligence Debate: False Starts, Real Foundation*, Cambridge, MA: The MIT Press.

Grossberg, S. (1987b), *The Adaptive Brain, II: Vision, Speech, Language and Motor-Control*, Amsterdam: Elsevier/North-Holland.

Grossberg, S. (1988), "Nonlinear Neural Networks: Principles, Mechanisms, and Architectures," *Neural Networks*, 1(1), 17-62.

Grossberg, S. (1987a), *The Adaptive Brain, I: Cognition, Learning, Reinforcement and Rhythm*, Amsterdam: Elsevier/North-Holland.

Hebb, D.O. (1949), "*Organization of Behavior*", New York, NY: John Wiley.

Hofstader, D.R. (1979), " *Godel, Escher, and Bach*, New York, NY: Bantom Books.

Hopfield, J.J. (1984), "Neurons with Graded Response have Collective Computational Properties Like Those of Two-State Neurons", *Proc. of Nat'l Acad. Sci.*, 81, 3058-3092.

Hopfield, J.J. and Tank, D.W. (1985), "Neural Computation and Constraint Satisfaction Problems and the traveling Salesman", *Biol. Cyber.*, 52, 141-152.

Hopfield, J.J. (1982), "Neural Networks and Physical Systems with Emergent Collective Computational Abilities", *Proc. Nat'l. Acad. Sci.*, 79, 2554-2558.

Kanal, L. and Tsao T. (1986), "Artificial Intelligence and Natural Perception", *Proc. of Intelligent Autonomous Systems*, Amsterdam, 60-70.

Kohonen, T. (1984), *Self-Organization and Associative Memory*, Berlin: Springer-Verlag.

Kohonen, T. (1987), "Adaptive, Associative, and Self-Organizing Functions in Neural Computing", *Applied Optics*, 26(23), 4910-4919.

Kohonen, T. (1988), "An Introduction to Neural Computing", *Neural Networks*, 1(1), 3-16.

Kohonen, T. (1982), "Self-Organized Formation of Topologically Correct Feature Maps", *Biol. Cybern*, 43, 59-70.

Kohonen, T. (1977), *Associative Memory: System Theoretic Approach*, Berlin: Springer-Verlag.

Ladd, S. (1985), *The Computer and the Brain: Beyond the Fifth Generation*, New York: Bantom Books.

Leibniz, J. (1951), *Selections*, Philip Wiener (Ed), New York, NY: Scribner.

Linsker, R. (1986). "From Basic Network Principles to Neural Architecture: Emergence of Orientation Columns", *Proc. Natn. Acad. Sci.*, 83, 8779-8783.

Linsker, R. (1986). "From Basic Network Principles to Neural Architecture: Emergence of Orientation-Selective Cells", *Proc. Nat'l. Acad. Sci.*, 83, 8390-8394.

Linsker, R. (1986), "From Basic Network Principles to Neural Architecture: Emergence of Spatial-Opponent Cells", *Proc. Nat'l. Acad. Sci.*, 3, 7508-7512.

Lippmann, R.P. (1987), "An Introduction to Computing with Neural Nets", *IEEE ASSP Magazine*, 4(2), 4.

McCulloch, W.S. and Pitts, W.H. (1943), "A Logical Calculus of the Ideas Immanent in Nervous Activity", *Bulletin of Mathematical Biophysics*, 5.115.

Minsky, M. (1967), *Computation: Finite and Infinte Machines*, New York, NY: Prentice-Hall.

Newell, A. and H. Simon (1976), "Computer Science as Empirical Inquiry: Symbols and Search", *Comm. ACM*.

Pearlmutter, B.A. (1989), "Learning State Space Trajectories in Recurrent Neural Networks", *Neural Computation*, 1(3), 263-269.

Rosenblatt, F. (1962), *Principles of Neurodynamics, Perceptrons and the Theory of Brain Mechanisms*, Washington, D.C: Spartan Books.

Toomarian, N. and J. Barhen (1992), "Learning a Trajectory Using Adjoint Functions, and Teacher Forcing", *Neural Networks*, 5(3), 473-484.

Weiner, N. (1948), *Cybernetics, Control and Communications in the Animal and the Machine*, New York, NY: John Wiley and Sons.

Williams, R.J., and D. Zipser (1989), "A Learning Algorithm for Continually Running Fully Recurrent Neural Networks", *Neural Computation*, 1(3), 270-280.

Winograd, S. and Cowan, J.D. (1963), *Reliable Computation in the Presence of Noise*, Cambridge, MA: The MIT Press.

Zak, M. (1988), "Terminal Attractors for Addressable Memory in Neural Networks," *Physics Letters A*, 133, No. 1,2, 18-22.

Zak, M. (1989), "Terminal Attractors in Neural Networks", *Int'l Jour. on Neural Networks*, 2(3),

Zak, M. (1989), "The Least Constraint Principle for Learning in Neurodynamics", *Phys. Lett. A*, 135, 25-28.

Zak, M. (1990), "Creative Dynamics Approach to Neural Intelligence", *Bio. Cyber.*, (in press).

Zak, M. (1990), "Weakly Connected Neural Networks", *Applied Math. Lett.*, 3(3),

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